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A Neural Network Approach to Electromyographic Signal Processing for a Motor Control Task

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Abstract

This paper proposes a novel signal processing technique employing both neural networks and classical signal processing methods to effectively map the surface electrical signal concomitant with muscle contraction (EMG) to human muscle activation. With a computational musculoskeletal model it is shown that these predicted muscle activations, accurately estimate joint torque for various ballistic flexion exercises. Through the systems ability to generalize across exercise trials and predict a classic ballistic triphasic activation pattern, a hybrid musculoskeletal system may be able to accurately and reliably model extremely complex physiological systems with clinical implications.

1. Introduction

Although EMG is simply a by-product of muscle activation [3], it is readily obtainable and is currently the only non-invasive indicator of muscle activation intensity. If the complex relationship between EMG and muscle force can be determined, it will provide researchers with accurate non-invasive access to human muscle forces. Such accurate estimations of muscle forces and joint stresses would provide engineers with valuable design parameters to be used in prosthetic limb and joint design. A non-invasive relationship between EMG and muscle force could also aid in the development of an EMG-driven above-elbow prosthesis [4] exploiting the synergistic nature of the human muscular system in movement coordination [4,5].

The complex relationship between EMG and the joint mechanical response can be broken down into three parts:
1) Observable EMG signal and muscle activations
2) Individual muscle activations and forces
3) Individual muscle forces and net joint torque.

While the second and third segments of this triad are modeled computationally as a four muscle, one degree of freedom (DOF) joint mechanical system, the first relationship is modeled separately as a neural network. This neural structure "pre-processes" and transforms experimental processed EMG into muscle activation data used to drive the musculoskeletal model and predict muscle forces and net joint torque. The complete hybrid system model is shown below in Figure 1.1.

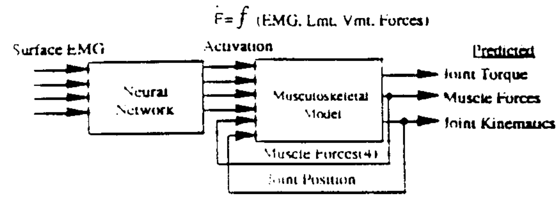


Figure 1.1: Complete Hybrid System Model

2. Musculoskeletal Model

This upper extremity model reduces the complexity of the motor control task to one DOF (flexion/extension) and four muscles: biceps, brachialis, brachioradialis and triceps. This reduction in DOF to a simple hinge joint does not produce results significantly different from other approaches consisting of two or more DOF [6]. Development of this musculoskeletal model for the upper extremity ensues from previous work to which the reader is referred [1,2,7,8,9 and 10].

3. Experimental Methods

A ballistic movement (a single maximally rapid flexion with an abrupt stop) was chosen over other movements to provide the system with distinct images of muscle activation patterns.

After digitally sampling at 1000 Hz, the surface EMG data were zero-mean averaged, full-wave rectified and low-pass filtered (f_c = 8 Hz). Other network input parameters dependent on human anthropometric data were obtained from [11]. Each neural network training set consisted of processed EMG, net joint torque, angular position and velocity.

4. Neural Networks

A multi-layer perceptron was used to model the relationship between the observable EMG data and muscle activations (Fig. 4.1). Batch error updating was used during all training sessions.

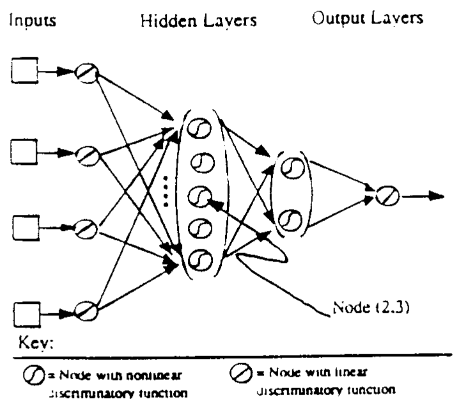
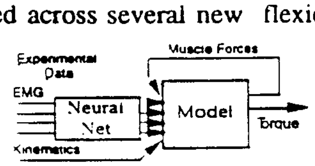


Figure 4.1: Typical Feedforward Network

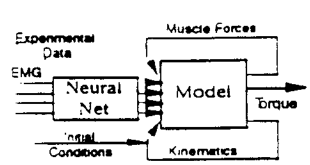
5. Results

Multiple tests were conducted using the hybrid Neural Network-Musculoskeletal Model:

- Open Loop, Single Trial: A single flexion trial is run in open-loop fashion by furnishing experimental kinematic data throughout the experimental trajectory (Figure 4.2, Open Loop).
- Closed Loop, Single Trial: A single ballistic flexion trial was run while furnishing only initial experimental angular position and velocity and allowing kinematic information to flow in a closed loop fashion (Figure 4.2, Closed Loop).
- Activation Loss Function: A neural loss function was employed to minimize both system torque error and overall muscle activation.
- Single Trial Generalization: A network was trained on a single ballistic flexion trial. The system's ability to generalize was evaluated by observing performance with new flexion data inputs.
- Multi-Trial Generalization: A network was trained across multiple ballistic flexion trials and was evaluated across several new flexion trials.



Open Loop



Closed Loop

Figure 4.2: Open vs. Closed Loop Configuration

5.1 Open Loop, Single Trial Network

After training the network on a single flexion data set in open loop configuration, a stable minimum was located resulting in a torque error coefficient of $\varepsilon=0.45$ as calculated in Equation 5.1.

$$\varepsilon = \sqrt{\frac{\Sigma(x_{\exp} - x_{\text{model}})^2}{\Sigma(x_{\exp})^2}} \tag{5.1}$$

From Figure 5.1, it can be seen that the major deviations between experimental data and system response are during the rapid deceleration and large negative net joint torque.

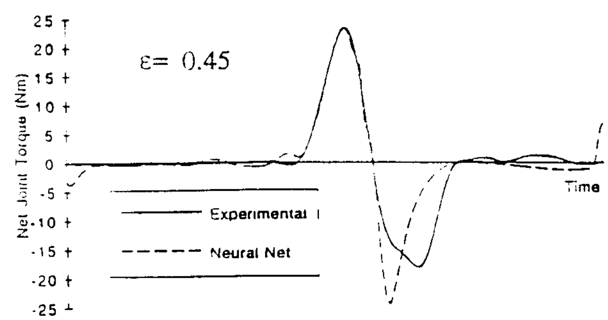


Figure 5.1: Single Flexion, Open Loop Results

In order to verify the validity of the network mapping, muscle activation curves (Figure 5.2) and force profiles which resulted in the torque trajectory were analyzed.

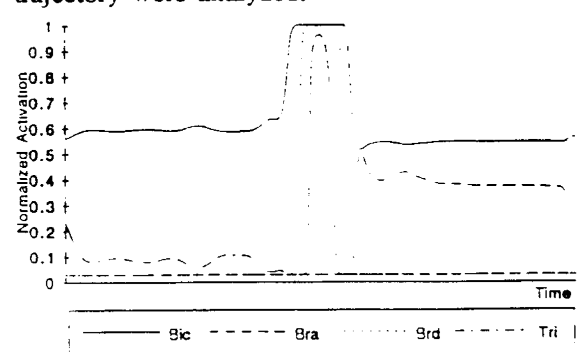


Figure 5.2: Resultant Muscle Activation

Figure 5.2, reveals that the neural network found a solution to the EMG to activation mapping problem that used the biceps as the primary flexor. Although the activation trajectories for this mapping resulted in an accurate torque profile, these activations and force profiles (not shown) do not exhibit the synergistic nature expected of a ballistic movement are not physiologically feasible. Because the elbow joint complex is a redundant system (there are more actuators than degrees of freedom), this mapping, although physiologically unrealistic, is a valid solution.

5.2 Closed Loop, Single Trial Network

To test the system's ability to converge on a solution in closed-loop configuration, kinematic output from the model was allowed cycle back into the system input. Instead of initializing the weight matrix to random values as is standard for a new neural network, the weight matrix was saved from the previous open loop trial and the system was allowed to train.

Subsequent training (with the same experimental data set) of the closed-loop configuration with low, stable weight updates resulted in a final torque error of $\varepsilon=0.28$ as shown in Figure 5.3.

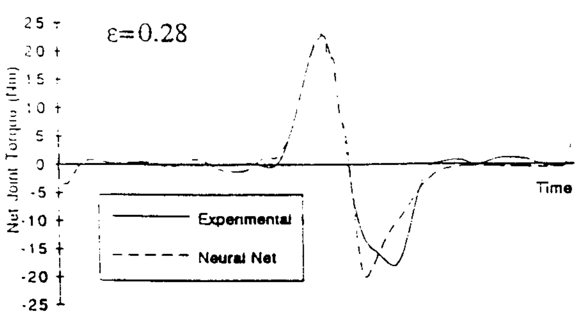


Figure 5.3: Single Flexion, Closed Loop Results

Although the mapping of the closed loop trial resulted in lower torque error than the open loop system, significant kinematic tracking errors arose. Because the network in this configuration used net joint torque as the sole "teacher" and basis for the network error function, the overall torque error is minimized without regard to joint kinematics. As a result, any discrepancies between experimental and model kinematics accumulated and resulted in inaccurate kinematic predictions.

5.3 Results with Activation Loss Function

Although the simulation results for the aforementioned trials were physiologically unrealistic, they were indeed valid for the predetermined loss function. In order to force the results to a physiologically realistic solution, an arbitrary activation loss function was added to the existing torque-error loss function. This change in loss function alters the weight space and, hence, alters both the minima in the weight space and the way the network learns. With the addition of this arbitrary activation loss function, the system error, J, becomes Equation 5.2.

$$J = \tfrac{1}{2}\left[(\Gamma - \Gamma_d)^2 + \varphi(a)\right] \qquad (5.2)$$

where: Γ = System Torque
Γ_d= Desired Torque
$\varphi(a)$= Activation. Loss Fn.

Because this new system loss function penalizes large activations (Equation 5.3) as well as torque error, the network tends to minimize both system torque error and overall network activation simultaneously.

$$\varphi(a) = k\left[(\varphi_1 a_{bic})^2 + (\varphi_2 a_{bra})^2 + (\varphi_3 a_{brd})^2 + (\varphi_4 a_{tri})^2\right] \quad (5.3)$$

where: k= a variable learning constant
φ_i= weighting functions
(currently $\varphi_1=\varphi_2=\varphi_3=\varphi_4=$ 1.0).

Because the human body tends to perform activities in a metabolically efficient manner, it can be hypothesized that if the overall muscle activation is reduced (while maintaining accurate torque tracking), then all muscle activations will "balance," resulting in an even distribution of work across all muscles. The activation loss function was chosen over other alternatives (minimizing jerk [12], effort [13], or torque-change [14] because muscle activation is independent of other muscle parameters, such as force and length, and is easily accessible.

After starting with a random weight space and repeating the same general training algorithm as in previous trials, the network converged with favorable results, ε= 0.197 (Figure 5.4).

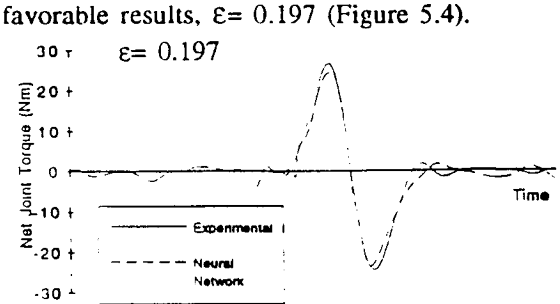


Figure 5.4: Tracking Results with Loss Function

These new activations, compared to those without the activation loss function, had a more balanced distribution (Figure 5.5) and were brought to full activation simultaneously and synergistically, as is the case with typical ballistic clinical data.

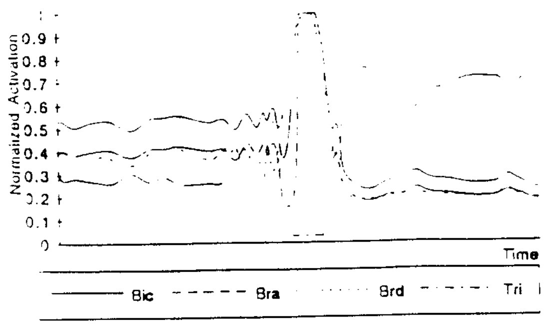


Figure 5.5: Activations with Loss Function

As expected from the activation trajectories, the individual muscle forces are also equally distributed across the three flexors (Figure 5.6).

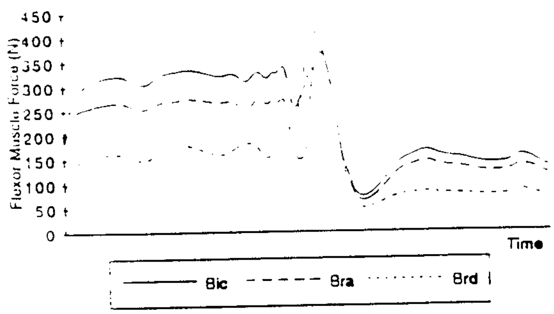


Figure 5.6: Flexor Forces for Loss Function Trial

5.4 Open Loop Single Trial Generalization

To test the system's effectiveness as a "smart" signal processing tool, a trained network with learning disabled in recall mode, was presented with new "unseen" flexion EMG data sets.
Although the system predicted the same general bipolar shape expected for a ballistic movement,, the tracking results were less accurate across the new trials (Table 5.1). These errors resulted from erroneous timing of the primary activation peak and temporal displacement of the torque waveforms.

Table 5.1: Single-Trial Generalization Results

Trial Number	Correlation Error, ε	Average Torque Error (Nm)
1*	0.428	2.081
2	1.551	6.245
3	1.922	9.595
4	1.820	8.119
5	1.417	6.949
6	2.257	9.784
7	1.036	5.875
8	1.900	7.575

*: Network trained on this trial

5.5 Open Loop Multi-Trial Generalization

The last test involved testing the system's ability to generalize. after training it on several trials (as opposed to one trial).The network, trained on five separate exercise trials until a correlation error function below 0.5 was reached, was tested across three new exercise trials (Table 5.2).

Table 5.2: Multi-Trial Generalization Results

Trial Number	Correlation Error, ε	Average Torque Error (Nm)
1*	0.422	1.979
6	0.829	3.952
7	2.125	12.502
8	0.706	3.406

*: Network trained on this trial and several others

Although, the tracking results are of considerable variability, these results are significantly better when compared to the single-trial generalization results. Most importantly, a classic agonist-antagonist-agonist (triphasic) muscle activation pattern [16] was observed in the brachialis, brachioradialis and the triceps muscles for both trial 6 and trial 8 (Figure 5.7). The appearance of this classic pattern indicates that the network is detecting underlying features common to typical ballistic EMG signals. Further, this triphasic pattern is observed across several trials and in trials in which the network did not originally train.

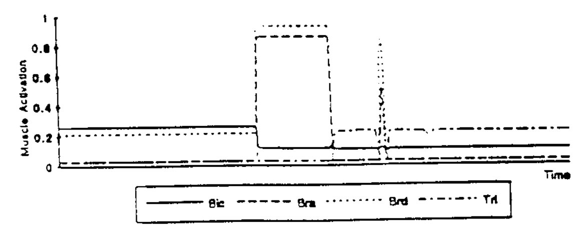


Figure 5.7: Muscle Activations from Multi-Trial Generalization

6. Discussion and Conclusions

The neural network-musculoskeletal model hybrid system was trained in several configurations and tested over a variety of situations ranging from simple open loop recall to closed loop generalization.

The open loop learning test resulted in an accurate torque profile, but the activation profiles were not physiologically feasible: the flexors did not act synchronously.

The closed loop trial resulted in significant destabilizing tracking errors for joint position and velocity due to positive feedback introduced from closing the kinematic loop and from integrating the resulting joint acceleration signal to arrive at joint velocity and position.

To correct for physiologically inaccurate activation trajectories in the open loop trial, an activation loss function was added to the system to aid the system in finding a solution whose force trajectories are physiologically realistic. Because it is extremely difficult to accurately measure individual human muscle forces *in vivo* during a similar movement, we can not clinically verify this conclusion given today's technology [15].

In the cross-trial generalization tests, even though system tracking accuracy was compromised, the system was able to predict the same general bipolar torque curve shape typical of ballistic movements.

The multi-trial generalization tests revealed the classic ballistic triphasic activation pattern indicating that the neural network was detecting underlying features common to typical ballistic EMG signals.

The results from this research indicate that a hybrid musculoskeletal system may be able to accurately and reliably model extremely complex physiological systems with clinical implications.

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